



# More Money for Less Time? Examining the Relative and Heterogenous Financial Returns to Non-Degree Credentials and Degree Programs

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There is a large and growing number of non-degree credential offerings between a high school diploma and a bachelor's degree, as well as degree programs beyond a bachelor's degree. Nevertheless, research on the financial returns to non-degree credentials and degree-granting programs is often narrow and siloed. To fill this gap, we leverage a national sample of individuals across nine MSAs and four industries to examine the relative financial returns to a variety of non-degree credentials and degree programs. Leveraging fixed-effect models, we explore the relationship between completing a credential or degree and earnings premiums. We find that an associate's, bachelor's, master's and doctorate degree follows a similar model of returns in which the number of schooling years is linearly related to proportional earnings premiums. However, students completing sub-baccalaureate certificates, post-baccalaureate certificates, and non-school credentials appear to get larger financial returns for less time. Furthermore, while the returns to both non-degree credentials and degree granting programs generally favored males over females and non-binary persons, this was not the case for race/ethnicity. Although individuals from Asian and White racial/ethnic groups often maintained an advantage in traditional education settings, Black individuals earned greater premiums from non-school credentials than White individuals, which may represent an opportunity to close racial/ethnic gaps in earnings.

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## More Money for Less Time?

### Examining the Relative and Heterogenous Financial Returns to Non-Degree Credentials and Degree Programs

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**Abstract.** There is a large and growing number of non-degree credential offerings between a high school diploma and a bachelor's degree, as well as degree programs beyond a bachelor's degree. Nevertheless, research on the financial returns to non-degree credentials and degree-granting programs is often narrow and siloed. To fill this gap, we leverage a national sample of individuals across nine MSAs and four industries to examine the relative financial returns to a variety of non-degree credentials and degree programs. Leveraging fixed-effect models, we explore the relationship between completing a credential or degree and earnings premiums. We find that an associate's, bachelor's, master's and doctorate degree follows a similar model of returns in which the number of schooling years is linearly related to proportional earnings premiums. However, students completing sub-baccalaureate certificates, post-baccalaureate certificates, and non-school credentials appear to get larger financial returns for less time. Furthermore, while the returns to both non-degree credentials and degree granting programs generally favored males over females and non-binary persons, this was not the case for race/ethnicity. Although individuals from Asian and White racial/ethnic groups often maintained an advantage in traditional education settings, Black individuals earned greater premiums from non-school credentials than White individuals, which may represent an opportunity to close racial/ethnic gaps in earnings.

**Keywords.** Education economics; financial returns; non-degree credentials

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## More Money for Less Time?

### Examining the Relative and Heterogenous Financial Returns to Non-Degree Credentials and Degree Programs

#### INTRODUCTION

Post-secondary education has been historically and causally linked to higher incomes (Card, 1999). In 2021, the median annual income for a year-round worker aged 25-34 with a high school diploma was \$39,700, while a worker of the same age with a bachelor's degree earned \$61,600 (National Center for Education Statistics, 2023). Indeed, having a bachelor's degree is often a good investment when compared to having no post-secondary education or training—especially over the life course (Deming, 2023). Unsurprisingly, large public investments, such as federal and state funding, have been made in educational institutions that offer bachelor's degrees. However, having a bachelor's degree does not necessarily guarantee getting a job that benefits from the earnings premium commonly associated with the degree. Although the unemployment rate for bachelor's degree holders is only one-third that of non-bachelor's degree holders, a significant portion of graduates still face *underemployment*. One analysis found that 52 percent of bachelor's degree holders were underemployed one year after graduation, and even after 10 years, 45 percent remained in jobs that did not fully utilize their degrees (Burning Glass Institute and Strada Institute for the Future of Work, 2024). Furthermore, there are large opportunity costs associated with earning a bachelor's degree—both in terms of time (e.g., most bachelor's degree programs take 4 years) and money (e.g., the average cost of attendance for a student living on campus at a public 4-year in-state institution is \$104,108; Hanson, 2024). For instance, in a recent survey of high school students, nearly half of them believed they could achieve professional success with education programs that lasted under 4 years (ECMC Group, 2022).

As a result, policymakers and researchers have continued to examine the economic returns of bachelor's degrees. Nevertheless, the perennial question of “Is college still worth it?” is limited in that it implies only a partially true counterfactual assumption; it relies on a comparison between having a bachelor's degree and having no post-secondary education and training whatsoever. However, there is a large and growing number of post-secondary education and training opportunities *between* a high school diploma and a bachelor's degree. Indeed, while Carnevale and his colleagues (2023) estimate that 72 percent of jobs will require some form of post-secondary education or training by 2031, not all these jobs will require a bachelor's degree. Even managerial and professional occupations (e.g., occupations in science, technology, engineering, and mathematics, social sciences, education, and healthcare), of which the vast majority—95 percent—require at least some form of post-secondary education and/or training, many of these jobs do not require a bachelor's degree (Carnevale et al., 2023). Rather, there is a substantial proportion of “middle-skill” jobs in the managerial and professional economy—that can be

obtained with post-secondary education and training opportunities *between* high school diploma to bachelor's degree, such as associate's degrees and non-degree credentialing programs that provide, for example, job- or industry-specific certifications. For instance, 23% of healthcare professional and technical occupations are projected to represent middle-skill jobs by 2031 (Carnevale et al., 2023).

At the same time, there is a large and growing number of jobs that require advanced skills, and subsequently, a large and growing number graduate degree programs. For example, when compared to the 7-percent average growth projection for employment in all occupations, employment in master's-level occupations was projected to grow by roughly 17 percent from 2016 to 2026, while employment in doctoral- and professional-level occupations was projected to grow by roughly 13 percent (BLS).

When considering the importance of post-secondary education and training *between* a high school diploma and a bachelor's degree, as well as *beyond* a bachelor's degree, a more comprehensive research approach is needed. Therefore, instead of interrogating whether college is still worth it, we examine the relative economic returns of a variety of non-degree credential programs and degree-granting programs. Furthermore, given changing labor market dynamics across industries, we explore the heterogenous returns across industries. Moreover, given the potential for non-degree credential programs to close gender and racial/ethnic equity gaps, we explore the heterogenous returns across various aspects of identity as well. To that end, we ask the following research questions:

1. What are the earnings premiums associated with earning a non-degree credential and completing a degree program?
2. To what extent does earning multiple credentials or degrees impact earnings premiums?
3. How do the earnings premiums associated with degree completion and non-degree credentials differ across industries?
4. How do the earnings premiums associated with degree completion and non-degree credentials differ by the recipients' gender and race/ethnicity?

In doing so, our analysis reflects the complexity of the educational choices, and their relative costs and benefits, faced by individuals, who are not just prospective students deciding between a high school diploma and a bachelor's degree, but are, instead, considering a range of post-secondary education and training opportunities over their life course. Although the evidence remains strong that bachelor's degree programs are associated with improved economic outcomes, it is essential to examine the returns of bachelor's program *relative* to the full array of education and training opportunities available.

## BACKGROUND

As described by Deming (2022) education, training, and experience—often referred to as human capital—explain a substantial share of the variation in earnings both within and across countries. While novel methods have been used to estimate earnings (e.g., instrumental variable approaches, regression discontinuity designs, etc.), Deming notes that these estimates match those produced by foundational methods (*ibid*). For example, the “Mincer Equation” (Mincer, 1976) specified an additive function for annual earnings that was linear in years of education and quadratic in years of work experience (Deming, 2022). Here, an additional year of schooling is estimated to produce a 6-18 percent increase in earnings, which has been largely replicated in more recent studies leveraging novel methods (*ibid*). Unsurprisingly, the earnings returns of associate’s, bachelor’s, master’s, and doctoral degrees—which are incremental in the number of years to complete—demonstrate incremental earnings returns that follow the Mincer Equation. Indeed, Deming demonstrates these incremental returns with the 1979 National Longitudinal Survey of Youth (Bureau of Labor Statistics, 2019): when controlling for ability, each additional year of schooling is associated with a 7 percent increase in earnings. Similarly, relative to not graduating high school, graduating high school is associated with a 13 percent increase in earnings; having some college (e.g., associate’s degree) is associated with a 25 percent increase in earnings; having a bachelor’s degree is associated with a 48 percent increase in earnings; and having a graduate degree is associated with a 54 percent increase in earnings (*ibid*).

Given the prevalence of degree-granting programs in the U.S., primarily consisting of associate’s, bachelor’s, master’s, and doctoral degrees, it is unsurprising that the research on the economic returns to education often focuses on these programs. However, there is an increasing number of non-degree credentials offered by various school- and non-school-providers. In 2023, Credential Engine, a non-profit organization that maps the terrain of credentials in the United States, estimated that there are roughly 1.076 million credentials offered by roughly 59,690 providers (Credential Engine, 2023). Non-Degree Credentials have been operationalized by National Skills Coalition (Duke-Benfield et al., 2019) as including (a) sub-baccalaureate credit bearing certificates that are earned from education institutions, (b) non-credit bearing certificates that are earned from community organizations (e.g., coding boot camps), (c) apprenticeship certifications that are earned through work-based learning opportunities and typically apply to industry trades and professions, (d) industry-recognized certifications that are earned from an industry certification body and typically demonstrate the ability to perform a specific job, and (e), licenses earned from a government agency based on a set of criteria that typically include some combination of degree attainment, certification, and assessment (Duke-Benfield et al., 2019, p. 6).

It is possible that non-degree credentials, which often entail one year (or less) of schooling, produce economic returns somewhere between a high school diploma and an associate’s degree, and thus follow the Mincer Equation. However, many of these credentials are structured differently than traditional degree-granting programs. For example, Coding Bootcamps attempt to condense the most applicable computer science skills into a 3-month credential program and often provide

direct connections to employment (e.g., through an apprenticeship). Recent research demonstrates that these non-degree credentials produce earnings returns that far exceed the estimates that we might expect from a Mincerian distribution. For example, Jabbari et al. (2023) found that a Coding Bootcamp produced a roughly 70 percent increase in earnings. Moreover, while degree programs are often sequential (e.g., in order to have a master's degree, one must first have a bachelor's degree) and onetime (e.g., it is rare for someone to earn two bachelor's degrees at two different time-points), non-degree credentials are often non-sequential and stackable. Indeed, both sub- and post-baccalaureate certificates are offered at many educational institutions, and non-degree credentials can be “stacked” on top of each other to demonstrate multiple domains of expertise.

In addition to the unique structure of non-degree credentials, the underlying mechanisms and subsequent populations are also distinctive. For example, because non-degree credentials are shorter than degree programs, they can often be more responsive to labor markets demands. In fact, many non-degree credentials are not offered by traditional education institutions and are instead offered by non-profit organizations and industry certification bodies. Moreover, as the opportunity costs—both in terms of time and money—are often lower in non-degree credentials, these credentials tend to serve a broader population of students. Indeed, many individuals who earn non-degree credentials are adults working full-time.

Given these dynamics, it is possible that the economic returns to non-degree credentials—relative to degree-granting programs—do not follow a Mincerian distribution. For instance, Jepsen, Troske, and Coomes (2014) leveraged fixed effects models with a sample of roughly 25,000 students from technical and community colleges in Kentucky, finding that non-degree certificates were associated within increased earnings; yet, the relative returns of non-degree certificates were substantially lower than the returns of an associate's degree. Men experienced a quarterly increase of \$297 for earning a certificate compared to \$1,484 for earning an associate's degree and women experienced a quarterly increase of \$299 for earning a certificate compared to \$2,363 for an associate's degree. Here, while earning a certificate represented a roughly 6 percent increase for men, earning an associate's degree represented a 29 percent increase; similarly, while earning a certificate represented roughly an 8 percent increase for women, earning an associate's degree represented a 65 percent increase. If a certificate, in theory, took half the time to complete as an associate's degree, then we would expect the percent increases for earning a certificate to be half of the percent increases for earning an associate's degree.

Additionally, Xu and Trimble (2016) leveraged fixed-effects models with a sample of roughly 230,000 students from 81 community colleges in Virginia and North Carolina to estimate the impact of sub-baccalaureate certificates, finding positive impacts on earnings. Following a Mincerian distribution, quarterly earnings increased from \$278 for earning a short-term certificate (i.e., a certificate lasting less than 1 year) to \$953 for earning a long-term certificate (i.e., a certificate lasting 1-2 years) to \$1,256 for earning an associate's degree in North Carolina. However,

in Virginia, the economic returns to long-term certificates (\$200) were considerably less than an associate's degree (\$773) and only slightly more than a short-term certificate (\$153).

Similarly, Bettinger and Soliz (2016) leveraged fixed-effects models with a sample of roughly 51,000 students from both technical and community colleges in Ohio, finding mostly positive impacts on earnings across multiple industries. However, while long-term certificates were associated with economic returns that were slightly less than associate's degrees—and thus loosely followed a Mincerian distribution, this was not the case for men or short-term certificates. Rather, men did not experience any significant economic returns for earning a long-term certificate, yet experienced economic returns for short-term certificates that were nearly twice the economic returns of an associate's degree. Further analyses demonstrated that the returns of short-term certificates were largely a byproduct of being offered by technical, rather than community, colleges.

Finally, Darolia, Guo, and Kim (2023) add nuance to the literature on economic returns of non-degree credentials by focusing on *very* short-term credentials. Leveraging fixed-effects models with matched samples of 108,000 students from community colleges in Kentucky, the authors found that very short-term credentials (requiring 6 credits or less) produce initial economic returns that are similar to short-term credentials (requiring 6-36 credits). In addition to research on initial economic returns to non-degree credentials, research has also examined long-term economic trajectories associated with non-degree credentials. For example, Minaya and Scott-Clayton (2022), leveraged fixed-effects models with roughly 92,000 students from community colleges in Ohio, finding that the economic returns to a long-term certificate remained flat when compared to the economic returns to an associate's degree, which grew over time.

The recent research on non-degree credentials provides three additional insights on human capital:

1. The relative economic returns to non-degree credentials do not necessarily follow a Mincerian distribution: the economic returns to non-degree credentials are not proportional to the time it takes to complete them.
2. The relative economic returns to non-degree credentials are context specific: the economic returns to non-degree credentials are informed by the industry and the geography in which they are used.
3. The relative economic returns to non-degree credentials are moderated by gender, meaning they are different for males and females.

As a result, it is important to consider the economic returns of non-degree credentials relative to a range of degree-granting programs, to take into account contexts relating to industry and geography, and to consider heterogeneous treatment effects across different dimensions of identity.

In this regard, we consider the relative returns of non-degree credentials compared to a wide range of degree-granting programs. We also consider differences between non-degree credentials offered by educational institutions and industries. Additionally, we include a population

of individuals across four unique industries and nine unique Metropolitan Statistical Areas (MSAs), and we consider differences by gender and race. Finally, given the ability to stack non-degree credentials, as well as on top of other degree granting programs, we explore the cumulative effects of earning multiple non-degree credentials. In doing so, we provide one of the first studies that (a) includes a range of degree granting programs and non-degree credentials from both educational institutions and industries, (b) includes a sample from a diverse array of U.S. cities, (c) examines heterogeneities across multiple dimensions of identity, and (d) examines cumulative effects from earning multiple non-degree credentials.

## **METHODS**

### **Data**

Our research focuses on individuals who obtained a non-degree credential or completed a degree program between 2017 and 2023. To obtain data for our analyses, we utilize two main sources: the National Student Clearinghouse (NSC) and a large credit bureau. The NSC provides comprehensive information on various credentials (i.e., undergraduate certificates and non-school-based certificates), in addition to earned degrees (e.g., associate's degree, bachelor's degree, master's degree, and doctoral/professional degrees), along with the month and year it was earned. While undergraduate certificates extend from education institutions that are nearly universally represented in NSC's database, this is not the case for non-school-based certificates, which are growing, but nevertheless, are relatively moderate in size within NSC's database. Currently, the most common non-school-based certificates within NSC's database were: Certified Pharmacy Technicians, Certified Safety Professionals, and Certified Welding Inspectors.

Through their online platform, the partnering credit bureau receives observed income—total gross annual earned income (calculated monthly)—directly from over 2.8mm businesses. In addition to income, the partnering credit bureau contains detailed employer information, including their North American Industry Classification System (NAICS) code. Due to data sharing arrangements across both the partnering credit bureau and NSC, our study sample originated on the credit bureau side; NSC data was then merged with the credit bureau data using individuals' personally identifiable information (PII); finally, the merged data was anonymized and shared with the research team through the credit bureau's online platform. Our sample had three main selection requirements:

- To ensure that earnings data was collected by the partnering credit bureau, individuals had to have observed income during the study period (i.e., 2017-2023);
- To ensure a variety of industries with adequate matches with credentials and degree programs, individuals had to have worked in one of the following industries in 2023: education, manufacturing, STEM, and healthcare;



- To ensure our sample was reflective of a broad array of geographic and economic contexts, individuals had to be working in one of nine metropolitan areas across the U.S. in 2023: San Francisco, CA; Denver, CO; Austin, TX; St. Louis, MO; Chicago, IL; Nashville, TN; Boston, MA; Philadelphia, PA; and New York City, NY.

For those that meet the three requirements, our analytic models focus on two groups of individuals as follows:

- *Treatment sample*: Those who earned any certificate(s) and/or degree(s) collected by the NSC between 2017-2023 (i.e., those whose certificates/degrees status has changed during the study period)
- *Comparison sample*: Those who never earned either a certificate or a degree collected by the NSC as of 2023 (i.e., those who are “unmatched” in the NSC sample<sup>1</sup>).

Our main analytic model focuses on within-person changes (i.e., through fixed effects) and thus leverages the treatment sample, while our supplemental analytic model focuses on both within- and between-person changes (i.e., through random effects).

For the individuals in question, we gathered total gross annual earned income as of the end of a year (December) from the partnering credit bureau. To construct the earnings income variable, we winsorized the annual earned income at \$609,351 (upper limit), based on the top U.S. tax brackets in 2024, to minimize the impact of extreme outliers. Also, because our current study focuses on income effects, as opposed to the combination of income and employment effects, we remove observations with zero annual gross income from the model. Our data from the partnering credit bureau and NSC also includes basic demographic information such as gender and race/ethnicity. After removing missing cases, our analytical sample consists of 948,878 yearly observations from 115,581 individuals. For a summary of the statistics of the variables used in our analytical model, please refer to Table 1 below.

**\*\* Table 1 is about here \*\***

#### *Degree and credential analysis*

In our analysis, we consider three types of non-degree credentials (sub-baccalaureate certificates, post-baccalaureate certificates, and non-school-based certificates) and four types of degree programs (associate’s degree, bachelor’s degree, master’s degree, and doctoral/professional degree) as independent but not mutually exclusive, such that an individual could earn multiple types of certificates and degrees at the same time. We also treat them as cumulative, such that an individual could earn multiple of the same types of certificates and degrees at different times.<sup>2</sup> For

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<sup>1</sup> Given NSC’s near complete reach of post-secondary students, non-matched persons most likely hold a high school diploma or less.

<sup>2</sup> There were no cumulative effects of non-school based certificates and post-baccalaureate certificates, given their relatively small population.

instance, we allow for John, in Table 2 below, to earn both an undergraduate certificate and an associate's degree in 2019, disregarding the association between these credentials and degrees, and instead allowing for earnings premiums to be estimated for both. Additionally, we assume that the impact of each earned credential and degree on income for John does not diminish over time but continues to extend beyond 2019. Finally, for individuals who achieve multiple credentials/degrees of the same type we assign a distinct code to each certificate—0 for credentials/degrees not earned, 1 for earning one/first certificate/degree, and 2 for earning multiple certificates; here, John earns a second undergraduate certificate in 2022.

**\*\* Table 2 is about here \*\***

## Empirical model design

For empirical analysis of the economic returns of education, we employ an individual fixed effect model. The fixed effect model approach addresses potential biases due to unobservable individual attributes, including demographic and socioeconomic characteristics. First, we assumed that income is a function of earning various types of credentials/degrees, in addition to individual characteristics. In mathematical representation,

$$y_{it} = \alpha_i + \sum_{c=1}^3 \sum_{n=1}^2 \beta^{cn} x_{it}^c + \sum_{d=1}^4 \sum_{n=1}^2 \gamma^{dn} x_{it}^d + \varepsilon_{it}$$

where an individual  $i$ 's annualized income in year  $t$ ,  $y_{it}$ , is a function of three types of earned credentials(s) and four types of degree(s) as of the start of the year,  $x_{it}^c$ , and  $x_{it}^d$ , respectively, in addition to individual fixed effects  $\alpha_i$ . To clarify the coding of the credential and degree variables, we assign the value  $n = 0$  to indicate credentials/degrees not earned,  $n = 1$  to indicate earning one/first credential/degree, and  $n = 2$  to indicate earning multiple credentials/degrees. Therefore, the coefficient estimates for each earned certificate/degree captures the average income changes associated with earning that specific certificate/degree, while accounting for fixed attributes of each individual. For example, the estimate  $\gamma^{41}$  represents the average income changes before and after earning a PhD degree. Similarly, the estimate  $\gamma^{42}$  represents the average income changes after earning two or more PhD degrees, compared to before earning any of the PhD degrees.

Second, we anticipate that the income effects of credentials/degree(s) vary across industry, and demographic characteristics. Therefore, we conduct three sets of subsample analyses to estimate heterogeneous income effects of certificates/degrees across four industries as of 2024 (manufacturing, STEM, education, healthcare); gender (male and female/other); and race/ethnicity (non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, and Hispanic). Lastly, we conduct a subsample analysis primarily focused on those without any degrees (i.e., AA, BA, MA/PhD).

The data analysis in this study was conducted using R version 4.3.3 (R Core Team, 2023) and we used a threshold of  $p < 0.05$ , 0.01, and 0.001 to assess statistical significance.

### *Interpretation Considerations*

It is important to note that the magnitude of the coefficient estimates cannot be *directly* equated across different types of degrees or certificates due to the potential for different baseline educational attainment. For example, one might observe that the coefficient estimate for holding a bachelor's degree ( $\beta=38,903$ ,  $p<0.001$ , Table 3, Column 1) is greater than the estimate for holding a master's degree ( $\beta=38,299$ ,  $p<0.001$ ) or a doctoral degree ( $\beta=36,966$ ,  $p<0.001$ ). Nevertheless, we cannot conclude that the actual monetary benefit of a bachelor is greater than that of a master's or a doctor degree based solely on this observation. This is because the reference period for the coefficient of a bachelor's degree includes the average pre-bachelor's degree annual income, which includes the time when individuals held an associate's degree, or a high school diploma. In contrast, the reference period for the coefficient of a PhD degree includes the average pre-PhD degree annual income, which includes the time when individuals held a master's or bachelor's degree. Let's consider Jane in Table 2 above: having earned a bachelor's degree in 2018, her reference period includes 2017 where she held an associate's degree; however, having earned a doctorate degree in 2022, her reference period includes 2017-2021 where she held an associate's degree (in 2017), a bachelor's degree (in 2018), and a master's degree (in 2020). Here, the annual income during the reference period for earning a PhD degree is likely to be considerably higher than the reference period for earning a bachelor's degree.

Rather, our use of income examines the *marginal* increases of earnings. For example, we can consider the *relative* advantage of earning an additional certificate or degree (e.g., the impacts of moving from a bachelor's degree to a master's degree relative to the impacts of moving from a master's degree to a PhD degree) with an understanding that the reference periods will be different. As the Mincer model includes both years of education years and years of work experience, we can infer general alignments to and misalignments from the Mincerian distribution of incomes in relationship to years of schooling, but we cannot fully approximate the Mincer model, as we cannot account for years of work experience, which may be further complicated by the potential for different pre-treatment time periods.

On the other hand, when comparing different levels of degree attainment within the same degree type (e.g., earning one bachelor's degree vs. earning two or more bachelor's degrees), the coefficient estimates can be directly equated because they share the same reference category, namely the period without a bachelor's degree. For instance, John's first non-degree credential (earned in 2019) and his second non-degree credential (earned in 2022) both share the same reference periods—2017-2018—where John had no non-degree credentials.

## EMPIRICAL FINDINGS

### Income effects

The first column in Table 3 presents the results from the fixed effect model, which examines within-individual changes in post-secondary education and their effects on earned income. Overall, we observe significant effects of non-degree credentials on earnings: a sub-baccalaureate certificate ( $\beta=\$38,996$ ,  $p<0.001$ ), a post-baccalaureate certificate ( $\beta=\$38,490$ ,  $p<0.001$ ), and a non-school certificate ( $\beta=\$32,253$ ,  $p<0.001$ ), and were all significantly associated with an average increase in annual gross income across our study period. Similarly, we observed significant effects of traditional degrees on earnings: an associate's degree ( $\beta=\$37,627$ ,  $p<0.001$ ), a bachelor's degree ( $\beta=\$38,903$ ,  $p<0.001$ ); a master's degree ( $\beta=\$38,299$ ,  $p<0.001$ ), and a doctoral degree ( $\beta=\$36,967$ ,  $p<0.01$ ) were all significantly associated with an average increase in annual gross income across our study period. In other words, the marginal returns of most non-degree credentials, as well as all traditional degrees was roughly \$37,000 to \$39,000; non-school credentials was slightly less with a marginal return of roughly \$32,000. We also observed additive effects of holding multiple credentials/degrees ranging from 183 percent (Bachelor's) to 215 percent (Associate's) of their original credential/degree effect.

**\*\* Table 3 is about here \*\***

### Heterogeneous income effects by industry

Columns 2 to 5 in Table 3 display the varied impact of different types of credentials and degrees across various industries. Overall, the returns of a traditional degree are greater in manufacturing (Column 4) and STEM (Column 5) industries compared to health care (Column 2) and education (Column 3). For instance, while the marginal returns of a bachelor's degree in manufacturing and STEM fields are more than \$50,000 a year (Manufacturing:  $\beta=\$52,262$ ,  $p<0.001$ ; STEM:  $\beta=\$57,772$ ,  $p<0.001$ ), those in the manufacturing and STEM fields are approximately \$30,000 a year (Health care:  $\beta=\$32,574$ ,  $p<0.001$ ; Education:  $\beta=\$28,580.890$ ,  $p<0.001$ ). Similar trends were observed for non-degree credentials, although not all estimates were significant, likely due to inflated standard errors resulting from smaller sample sizes. For example, the marginal returns of a non-school credential in STEM ( $\beta=\$76,867$ ,  $p<0.001$ ) was more than twice the marginal returns in health care ( $\beta=\$34,875$ ,  $p<0.001$ ), yet non-significant in education and manufacturing.

### Heterogeneous income effects by demographic characteristics

Table 4 reports the heterogeneous income effects based on gender (Columns 1-2) and race/ethnicity (Columns 3-6). When examining gender-based differences in economic returns, we observe consistent gender disparities in income effects across non-degree credentials and traditional degrees. Across all credential/degrees, the returns on education for male participants are greater

than those for female/non-binary persons, ranging from 29.4% greater for a sub-baccalaureate certificate to 36.5% greater for a doctoral degree).

There are also observed heterogeneous income effects of credentials and degrees across race and ethnicity. Asians consistently demonstrated the largest returns to non-degree credentials, with the exception of non-school certificates, which was not significant—likely due to inflated standard errors resulting from smaller sample sizes. A similar trend was observed for more traditional degrees, although the pattern for first degrees became uniform across all degree types: Asian individuals earned more than White individual, who earned more than Hispanic individuals, who earned more than Black individuals. For instance, obtaining a bachelor’s degree resulted in a \$56,865 increase for Asian individuals, followed by \$39,509 increase for White individuals, a \$30,365 increase for Hispanic individuals, and a \$27,882 increase for Black individuals. However, outside of traditional education systems, this pattern did not hold. Most notably, Black individuals earned greater premiums from non-school credentials than White individuals (Black:  $\beta$ =\$34,230,  $p < 0.01$ ; White:  $\beta$ =\$31,308,  $p < 0.001$ ).

## DISCUSSION

In addition to low-skill jobs (e.g., that are typically filled with high school diploma holders) and high-skill jobs (e.g., that are typically filled with bachelor degree holders), there is a large and growing number of jobs that require “middle”, as well as “advanced”, skills. In response to these jobs, there is a large and growing number of educational offerings *between* a high school diploma and a bachelor's degree, as well as degree programs *beyond* a bachelor’s degree. Moreover, even though non-degree credentials—from a skills perspective—often lie between a high school diploma and a bachelor’s degree, they tend to operate uniquely. These credentials are not always sequential. For example, one doesn’t need a high school diploma to earn a non-degree credential, and non-degree credentials can be earned by individuals with more advanced degrees. Furthermore, some non-degree credentials, such as post-baccalaureate certificates, can offer opportunities to learn no skills for students who are returning to post-secondary education but can’t commit the time or tuition towards completing a formal degree. Moreover, non-degree credentials tend to be stacked (i.e., different credentials are earned at different time points) more often than more traditional degrees programs. Nevertheless, research on the financial returns to non-degree credentials and degree-granting programs is often narrow and siloed. As a result, it is difficult to ascertain the relative returns to a variety of post-secondary educational options. We, therefore, leverage a national sample of individuals across nine MSAs and four industries to examine the relative financial returns to a variety of non-degree credentials and degree programs.

### Summary of findings

First, leveraging a fixed-effect models, we explore the average earnings premium across our study period resulting from an individual earning a degree or credential. While it is difficult to replicate a

Mincer model of financial returns to education based on our data and methods, we find that an associate's, bachelor's, master's and doctorate degree follows a similar model of returns in which the number of schooling years is linearly related to proportional earnings premiums—especially if we conceptualize each successive degree as taking a similar amount of additional time if a student is enrolled full time (e.g., a bachelor's degree taking two more years than an associate's degree, a master's degree taking two more years than a bachelor's degree, and a doctorate/professional degree taking two more years than a master's degree<sup>3</sup>).

However, sub-baccalaureate certificates (\$38,996), post-baccalaureate certificates (\$38,490), and non-school credentials (\$32,252) appear to actually resemble the earnings increases of a two-year degree-granting program. In other words, students completing sub-baccalaureate certificates and earning non-school credentials appear to earn more money (proportionally) for less time—relative to other degree granting programs. Nevertheless, time-to-completion is difficult to verify for sub-baccalaureate certificates, post-baccalaureate certificates, and non-school credentials in our sample. While the literature would suggest that these certificates and credentials tend to require between 6 and 18 months to complete, the range of potential completion times is large.

Across all credential and degree programs, we observed cumulative effects that were substantially larger than the effects of earning a single credential or completing a single degree program in their respective categories. While sample constraints limit our ability to observe cumulative effects of non-school credentials and postbaccalaureate certificates, this finding demonstrates the importance of additional educational attainment—not only from advancing to *another* education level, but also from completing an additional credential or degree program *within* a given level. Here, the ability to “stack” educational credentials may allow for greater flexibility in skill attainment and thus greater adaptability to local labor markets.

While the returns on degree completions were often higher in Manufacturing and STEM industries, these returns were still significant in Education and Healthcare industries. Nevertheless, the returns to non-school credentials were only significant in STEM and Healthcare, potentially highlighting the importance of these credentials for career advancement in these fields. Additionally, regarding differences in financial returns according to gender, there were notable differences across degree programs as well as non-degree credentials, with males receiving larger returns than females and non-binary persons. Finally, in terms of race/ethnicity, while Asian individuals generally experienced the highest financial returns from education of all types, it is important to note that individuals from Hispanic and Black groups exhibited the lowest returns on traditional degrees, respectively; these returns were not only far lower than Asian individuals, but White individuals as well. Thus, even though traditional education can be seen as promoting social

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<sup>3</sup> Here, it is important to note that there are a variety of factors that can influence time-to-degree completion for students pursuing master's and doctorate/professional degrees, including type of degree, area of study, student status (e.g., full-/part-time), etc. For example, completing a law degree typically takes three years; completing a medical degree typically takes four years, and completing a PhD degree typically takes six years.

mobility, inequality may be effectively maintained within this system. Nevertheless, it is worth noting that these trends did not hold outside of the traditional education system: Black individuals earned greater premiums from non-school credentials than White individuals, which may represent an opportunity to close racial/ethnic gaps in earnings.

## **Implications**

These findings have significant implications for education finance and policy. Concerning education finance, our findings suggest a significant departure from a linear distribution of income according to years of schooling (e.g., like those based on the Mincer model) for non-degree credentials. Sub-baccalaureate certificates, post-baccalaureate certificates, and non-school credentials appear to demonstrate similar earnings increases as two-year degree programs despite often taking one year to complete, suggesting higher proportional earning premiums relative to the time it typically takes to complete these programs. Moreover, while the returns to both non-degree credentials and degree granting programs generally favored males over females and non-binary persons, this was not the case for race/ethnicity. Although individuals from Asian and White racial/ethnic groups often maintained an advantage in traditional education settings, Black individuals earned greater premiums from non-school credentials than White individuals, which may represent an opportunity to close racial/ethnic gaps in earnings. As a result, policymakers should consider making public investments across a range of non-degree programs, as opposed to a narrow focus on 2- and 4-year programs. Finally, our findings demonstrate the potential of leveraging and merging large sources of administrative data from credit agencies with administrative education data to demonstrate financial returns. While many studies rely on records from state unemployment insurance and individual education institutions, these data are often confined to particular states and schools, which can limit generalizability.

## **Limitations**

While our study offers one of the first nation-wide reports on the relative returns of both degree programs and non-degree credentials across multiple industries, it is not without limitations. Concerning external validity, our sample originated from a large credit bureau, and although it is extensive, it is not exhaustive. It is also important to note that our sample consisted of individuals with observed income in 2024, which does not include individuals who were unemployed throughout the year, and thus does not represent the entire adult population. In addition, we only consider individuals working in four specific industries; thus, it is possible that the economic returns to both degree programs and non-degree credentials are different in other industries. Another limitation is the use of NAICS codes, which are employer-specific, to identify employee industries. Indeed, one can work for an employer in a specific industry, yet not perform a core industry duty (and vice-versa).

Concerning internal validity, our sample employs a unit fixed effect model, rather than a two-way (i.e., unit plus time) fixed effect (TWFE) model, to capture the marginal income effects

credential or degree attainment. While TWFE models can be particularly useful for adjusting to potential macro-economic impacts, including inflation and other labor market dynamics, these models can bias results when time is endogenous to the treatments and outcomes under study, which is often the case in labor market returns research. For instance, in our study context, the time component (calendar year) is endogenous to both the treatment (i.e., when the credential or degree is attained) and the outcome (i.e., annual income). Therefore, time fixed effects could bias (or “soak up”) the treatment effects in our study—especially when considering the relatively short window in which we observe individuals: individuals in our study sample have earned at least one credential or degree within the seven-year window.

At the same time, the individual fixed effect model without a time control has limitations. One such limitation is that the estimated income effects include natural wage increases (e.g., resulting from inflation) in addition to the returns from education. Thus, we also employ a random effect modeling approach, which leverages between-individual comparisons and thus accounts for natural wage increases (Appendices A). Although our control group, consisting of individuals who have never earned any credential or degree during the study period, could be systematically different from our treatment groups, the comparison of income effect estimates from the fixed and random effect models is compelling and generally supports our modeling approach. For example, our fixed effect model estimates the impact of a bachelor’s degree to be \$38,903 ( $p < 0.001$ ), while the random effect model estimates it to be \$36,261 ( $p < 0.001$ ). The gap between the two estimates, \$2,642, is somewhat comparable to natural wage increases, given the average annual wage of \$91,045 and a conventional 3 percent wage increase. Most importantly, the trends and patterns in our random effect models mostly reflect those from our fixed-effects models, suggesting that the findings from our fixed-effect models are not merely reflections of natural wage increases

Additionally, it is likely that students “select” certain degree programs and non-degree credentials based on a variety of observed and unobserved characteristics. While our fixed effects models account for person-specific confounders, we cannot rule out the possibility of other, unobserved confounders that may bias our results. Future research should consider leveraging pre-treatment information relating to interest and ability, such as academic course-taking and performance in high school. It is also important to note that we cannot identify the length of time it takes for each individual to complete their respective degree or earn their respective credential in our data, which limits our ability to factor in exact opportunity costs related to time. Future research should consider ways to capture length of credential/degree completion to better understand these costs. Finally, it is possible that individuals in our sample have earned non-degree credentials from other credentialing bodies that are not identified by the NSC, which may bias our results—especially our results pertaining non-degree credentials. While the data on sub- and post-baccalaureate certificates, as well as degree granting programs, is near-exhaustive in the NSC database, the data on non-degree credentials is not. Future research should consider leveraging additional sources of data for non-degree credentials.



## CONCLUSION

In 2021, only 37.9 percent of adults aged 25 and older had a bachelor's degree (Schaeffer, 2022), and nearly 40 percent of all students that started a bachelor's degree program failed to graduate (National Center for Education Statistics, 2021). Given the growing economic opportunities for middle-skill workers and the deleterious effects of student debt—especially for individuals who fail to earn a degree (Jabbari et al., 2023), research on non-degree credentials is particularly important for increasing social mobility. In addition to increasing social mobility, research on non-degree credentials is also important for increasing racial equity. As only 28.1 percent of Black adults and only 20.6 percent of Hispanic adults have a bachelor's degree (Schaeffer, 2022), post-secondary education and training *between* a high school diploma and a bachelor's degree may represent a viable and desirable educational opportunity for groups that have been historically excluded. Finally, broader educational attainment can also increase community prosperity, as research demonstrates that employers tend to locate to areas with large pools of skilled labor (Takatsuka, 2011) and local sectors tend to attract new firms when training costs are borne by workers (Almazan et al., 2007).

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## TABLES

**Table 1. Summary statistics of the variables in use**

	All (n=115,581)		Healthcare (n=52,198)		Education (n=23,943)		Manufacturing (n=27,397)		STEM (n=12,043)	
	2017	2023	2017	2023	2017	2023	2017	2023	2017	2023
<b>Credentials</b>										
Sub-Baccalaureate Certificate (SC)	0.016 (0.132)	0.057 (0.247)	0.017 (0.139)	0.060 (0.256)	0.014 (0.124)	0.053 (0.239)	0.015 (0.128)	0.053 (0.238)	0.014 (0.126)	0.056 (0.246)
Post- Baccalaureate Certificate (PC)	0.0000 (0.003)	0.0003 (0.017)	0.0000 (0.004)	0.0003 (0.018)	0.0000 (0.000)	0.0002 (0.014)	0.0000 (0.000)	0.0004 (0.019)	0.0000 (0.000)	0.0002 (0.013)
Non-School Credential (NSC)	0.0001 (0.007)	0.0004 (0.020)	0.0001 (0.009)	0.0003 (0.000)	0.0000 (0.000)	0.0004 (0.019)	0.0000 (0.006)	0.0005 (0.022)	0.0001 (0.009)	0.0005 (0.022)
<b>Degrees</b>										
Associate's Degree (AA)	0.012 (0.115)	0.041 (0.209)	0.013 (0.119)	0.043 (0.216)	0.012 (0.113)	0.039 (0.201)	0.011 (0.110)	0.040 (0.206)	0.012 (0.114)	0.039 (0.204)
Bachelor's Degree (BA)	0.049 (0.261)	0.234 (0.533)	0.054 (0.277)	0.244 (0.551)	0.042 (0.233)	0.223 (0.509)	0.046 (0.251)	0.225 (0.522)	0.050 (0.264)	0.232 (0.531)
Master's Degree (MA)	0.014 (0.124)	0.064 (0.261)	0.015 (0.129)	0.066 (0.266)	0.013 (0.122)	0.062 (0.256)	0.013 (0.123)	0.062 (0.257)	0.012 (0.111)	0.064 (0.257)
Doctoral Degree (DR)	0.005 (0.074)	0.024 (0.158)	0.006 (0.078)	0.026 (0.163)	0.005 (0.071)	0.023 (0.155)	0.004 (0.068)	0.023 (0.151)	0.006 (0.078)	0.024 (0.156)
<b>Income</b>										
Annual Income (top-coded at \$609,351)	52585.6 (79031.6)	122037.5 (114606.6)	47156.3 (65669.0)	106806.5 (94342.0)	41115.7 (67895.0)	91095.5 (100980.0)	66628.6 (96983.8)	162252.4 (134489.6)	66974.2 (98225.1)	163708.7 (134665.6)
<b>Gender</b>										
Female/other	0.603 (0.489)		0.743 (0.437)		0.622 (0.485)		0.382 (0.486)		0.460 (0.498)	
<b>Race</b>										
White	0.667 (0.471)		0.624 (0.484)		0.694 (0.461)		0.709 (0.454)		0.708 (0.455)	
Black	0.098 (0.297)		0.131 (0.338)		0.087 (0.282)		0.061 (0.238)		0.056 (0.229)	
Hispanic	0.129 (0.335)		0.149 (0.356)		0.101 (0.301)		0.127 (0.333)		0.101 (0.302)	
Asian	0.011 (0.104)		0.014 (0.117)		0.010 (0.098)		0.008 (0.087)		0.008 (0.090)	

**Table 2. Data Structure for Identifying Treatment Status**

Name	Year	Sub- Baccalaureate Certificate	Post- Baccalaureate Certificate	Non-School- Credential	Associate's Degree	Bachelor's Degree	Master's Degree	Doctorate
<i>John</i>	2017	0	0	0	0	0	0	0
<i>John</i>	2018	0	0	0	0	0	0	0
<i>John</i>	2019	1	0	0	1	0	0	0
<i>John</i>	2020	1	0	0	1	0	0	0
<i>John</i>	2021	1	0	0	1	0	0	0
<i>John</i>	2022	2	0	0	1	0	0	0
<i>John</i>	2023	2	0	0	1	0	0	0
<i>Jane</i>	2017	0	0	0	1	0	0	0
<i>Jane</i>	2018	0	0	0	1	1	0	0
<i>Jane</i>	2019	0	0	0	1	1	0	0
<i>Jane</i>	2020	0	0	0	1	1	1	0
<i>Jane</i>	2021	0	0	0	1	1	1	0
<i>Jane</i>	2022	0	0	0	1	1	1	1
<i>Jane</i>	2023	0	0	0	1	1	1	1

**Table 3. Income impacts of certificates and degrees (FE effects; by industry)**

	All		By Industry				
		Healthcare	Education	Manufacturing	STEM		
	(1)	(2)	(3)	(4)	(5)		
<b>Credentials</b>							
SC	38,995.750 *** (630.661)	32,736.890 *** (784.933)	28,909.150 *** (1202.824)	51,493.380 *** (1673.899)	60,561.180 *** (2321.717)		
SC <sup>M</sup>	74,427.870 *** (2571.955)	67,039.460 *** (3104.122)	58,416.330 *** (5395.141)	91,293.920 *** (6875.432)	100,210.200 *** (9155.179)		
PC	38,490.240 *** (7247.634)	24,748.630 ** (9327.718)	45,954.280 ** (14168.770)	48,447.440 ** (15834.640)	76394.98 (41672.750)		
NSC	32,252.880 *** (6638.192)	34,875.370 *** (10512.960)	19887.85 (11800.670)	18346.91 (14162.420)	76,866.720 *** (21524.120)		
<b>Degrees</b>							
AA	37,627.390 *** (736.186)	31,042.780 *** (911.164)	31,563.420 *** (1429.860)	49,552.730 *** (1922.278)	54,038.640 *** (2781.427)		
AA <sup>M</sup>	80,976.310 *** (3282.647)	59,105.610 *** (3938.936)	70,648.470 *** (6968.232)	116,617.900 *** (8753.746)	130,850.900 *** (11858.410)		
BA	38,903.430 *** (313.142)	32,574.790 *** (396.604)	28,580.890 *** (586.228)	52,261.840 *** (813.184)	57,772.230 *** (1158.389)		
BA <sup>M</sup>	71,110.490 *** (815.010)	60,407.010 *** (1011.241)	53,932.430 *** (1554.168)	94,567.100 *** (2173.924)	102,961.800 *** (3016.196)		
MA	38,299.330 *** (569.709)	31,359.620 *** (722.092)	27,945.690 *** (1075.505)	53,624.850 *** (1488.787)	54,459.430 *** (2042.076)		
MA <sup>M</sup>	68,686.200 *** (2395.102)	57,289.820 *** (2982.664)	50,408.050 *** (4427.228)	103,537.300 *** (6220.886)	79,753.950 *** (9920.095)		
DR	36,966.570 *** (915.992)	30,852.270 *** (1141.678)	29,019.740 *** (1741.367)	49,530.480 *** (2397.298)	54,469.440 *** (3475.729)		
DR <sup>M</sup>	67,263.720 *** (5929.276)	53,820.480 *** (6556.226)	67,415.670 *** (11345.400)	82,209.430 *** (20545.820)	137,572.000 *** (26701.470)		
Individual fixed effect	Y	Y	Y	Y	Y		
Observations	948,878	425,812	202,050	217,963	103,053		
R2	0.04	0.039	0.03	0.045	0.057		
F Statistic	2,728.015 ***	1,213.497 ***	428.983 ***	717.767 ***	432.361 ***		

**Note:** \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

M: Multiple credentials/degrees.

**Table 4. Income impacts of certificates and degrees (FE model, by demography)**

	By Gender		By Race/Ethnicity			
	Male (1)	Female (2)	White, NH (3)	Hispanic (4)	Asian, NH (5)	Black, NH (6)
<b>Credentials</b>						
SC	45,294.880 *** (1175.109)	35,005.800 *** (706.670)	39,813.900 *** (782.671)	31,413.540 *** (1432.709)	60,216.570 *** (2645.417)	21,801.660 *** (1451.672)
SC <sup>M</sup>	75,573.090 *** (4731.352)	74,112.400 *** (2906.293)	75,903.350 *** (3023.958)	68,964.650 *** (6933.410)	92,707.550 *** (12974.560)	47,821.130 *** (6414.312)
PC	42,291.960 *** (11455.480)	32,481.310 *** (9374.136)	28,127.910 ** (9964.144)	26,803.040 * (12670.980)	95,667.980 *** (28341.140)	48,777.530 *** (14117.860)
NSC	35,941.120 ** (11905.980)	28,939.650 *** (7633.950)	31,307.680 *** (8145.453)	31,540.63 (16163.680)	46,705.06 (41175.710)	34,229.500 ** (11844.570)
<b>Degrees</b>						
AA	44,766.780 *** (1373.187)	33,156.630 *** (824.352)	38,147.680 *** (915.806)	30,550.510 *** (1647.872)	51,895.840 *** (3130.283)	29,199.560 *** (1680.780)
AA <sup>M</sup>	110,445.900 *** (6208.550)	63,101.850 *** (3644.811)	83,942.210 *** (4125.712)	73,435.070 *** (7968.137)	108,755.900 *** (13577.240)	56,830.020 *** (6648.977)
BA	45,522.050 *** (580.539)	34,631.950 *** (352.027)	39,508.850 *** (391.176)	30,365.320 *** (688.251)	56,865.140 *** (1302.752)	27,882.340 *** (726.750)
BA <sup>M</sup>	83,768.790 *** (1506.783)	62,961.320 *** (917.884)	71,957.950 *** (1008.737)	53,407.700 *** (1853.254)	102,335.900 *** (3469.271)	55,846.820 *** (1887.233)
MA	45,589.320 *** (1063.392)	33,749.690 *** (637.671)	39,098.110 *** (709.826)	32,241.770 *** (1244.394)	53,057.650 *** (2374.481)	26,456.260 *** (1354.125)
MA <sup>M</sup>	82,097.820 *** (4509.010)	60,416.890 *** (2666.563)	68,282.230 *** (2970.997)	54,005.660 *** (5839.820)	109,956.900 *** (9531.957)	44,616.710 *** (5278.541)
DR	44,381.870 *** (1727.831)	32,512.790 *** (1018.554)	38,551.890 *** (1151.549)	27,952.630 *** (1924.953)	51,659.700 *** (3806.092)	23,130.350 *** (2213.677)
DR <sup>M</sup>	90,586.960 *** (11502.800)	54,962.140 *** (6485.340)	66,324.080 *** (7531.718)	62,211.230 *** (14163.630)	79,065.480 *** (20759.240)	69,287.800 *** (16050.310)
<b>Individual fixed effects</b>	Y	Y	Y	Y	Y	Y
Observations	376,767	572,111	630,165	123,856	94,585	89,221
R2	0.040	0.041	0.040	0.039	0.047	0.039
F Statistic	1,086.137 ***	1,716.309 ***	1,822.511 ***	347.594 ***	325.665 ***	253.364 ***

**Note:** \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

M: Multiple credentials/degrees.

## APPENDICES

### Appendix 1. Income impacts of certificates and degrees (RE effects; by industry)

	All		By Industry			
		HealthCare	Education	Manufacturing	STEM	
	(1)	(2)	(3)	(4)	(5)	
<b><u>Certificates and Credentials</u></b>						
SC	33,728.270 *** (579.672)	27,760.720 *** (718.417)	24,969.080 *** (1103.802)	43,108.210 *** (1531.492)	55,758.790 *** (2131.577)	
SC <sup>M</sup>	55,977.420 *** (2315.453)	48,193.370 *** (2770.639)	43,161.230 *** (4762.257)	67,782.780 *** (6226.121)	85,613.690 *** (8379.939)	
PC	41,835.420 *** (6941.459)	25,507.330 ** (8781.310)	49,558.990 *** (13787.240)	58,289.020 *** (15227.060)	68,388.26 (40829.120)	
NSC	31,789.900 *** (6189.648)	29,272.530 ** (9377.591)	20,055.74 (11210.010)	21,544.95 (13478.440)	73,373.130 *** (20013.740)	
<b><u>Degrees</u></b>						
AA	32,347.720 *** (671.167)	26,646.350 *** (828.699)	26,235.580 *** (1294.303)	42,863.430 *** (1745.112)	46,272.500 *** (2527.860)	
AA <sup>M</sup>	63,171.340 *** (2954.826)	44,213.390 *** (3509.215)	56,685.600 *** (6267.660)	94,273.600 *** (7850.589)	100,380.100 *** (10792.330)	
BA	36,262.600 *** (300.970)	30,101.640 *** (380.323)	26,642.990 *** (563.325)	48,897.760 *** (781.013)	53,711.490 *** (1111.775)	
BA <sup>M</sup>	60,666.500 *** (750.526)	49,978.330 *** (924.771)	46,510.590 *** (1432.680)	82,073.180 *** (1999.967)	88,749.820 *** (2774.370)	
MA	34,331.950 *** (530.828)	27,344.490 *** (669.130)	25,899.190 *** (1000.059)	47,774.880 *** (1384.358)	50,099.780 *** (1911.700)	
MA <sup>M</sup>	55,306.880 *** (2208.331)	44,614.290 *** (2711.658)	43,549.730 *** (4096.970)	83,167.710 *** (5758.292)	66,023.870 *** (9288.338)	
DR	32,672.310 *** (843.429)	27,337.130 *** (1045.721)	25,454.220 *** (1597.681)	43,872.570 *** (2211.521)	47,584.270 *** (3181.721)	
DR <sup>M</sup>	56,984.760 *** (5494.787)	45,412.540 *** (6110.059)	59,078.770 *** (10529.340)	83,167.710 *** (5758.292)	102,385.700 *** (22645.730)	
<b><u>Individual fixed effect</u></b>	Y	Y	Y	Y	Y	
<b><u>Group fixed effect</u></b>	Y	Y	Y	Y	Y	
<b>Constant</b>	58,086.600 *** (461.193)	51,752.010 *** (565.188)	45,394.970 *** (866.424)	77,148.590 *** (1165.327)	73,232.240 *** (1697.636)	
Observations	948,878	425,812	202,050	217,963	103,053	
R2	0.028	0.027	0.022	0.033	0.041	
F Statistic	29,290.760 ***	12,740.660 ***	4,624.438 ***	7,758.198 ***	4,750.849 ***	

**Note:** \*p<0.05; \*\*p<0.01; \*\*\*p<0.001  
M: Multiple credentials/degrees.